CLASSIFICATION OF ARTISANAL SMALL SCALE GOLD MINING SITES IN UPPER MAZARUNI, GUYANA 1986-2011

A Thesis submitted to the faculty of
San Francisco State University
In partial fulfillment of
the requirements for
the Degree

Master of Science

In

Geographic Information Science

by

Biniam Semere Mengisteab

San Francisco, California

May 2015

CERTIFICATION OF APPROVAL

I certify that I have read Classification of Artisanal Small Scale Gold Mining Sites in Upper Mazaruni, Guyana 1986-2011 by Biniam Semere Mengisteab, and that in my opinion this work meets the criteria for approving a thesis submitted in partial fulfillment of the requirement for the degree Master of Science in Geographic Information Science at San Francisco State University.

Leonhard Blesius, Ph.D.
Associate Professor of Geography

Xiao Hang Liu, Ph.D.
Associate Professor of Geography

Logan Hennessy, Ph.D.
Associate Professor of Liberal Studies

CLASSIFICATION OF ARTISANAL SMALL SCALE GOLD MINING SITES IN UPPER MAZARUNI, GUYANA 1986-2011

Biniam Semere Mengisteab
San Francisco, California
2015

Artisanal and small-scale gold mining activities (ASM) have grown significantly with a spike in markets over the past few decades. However, the spatial extent and environmental impacts of these activities are poorly known. Some recent studies suggest the need for appropriate scientific techniques to estimate these impacts. The study area of Jawalla village in Guyana's Upper Mazaruni River Basin was selected for the following reasons: 1) documented growth in ASM-based production, 2) the country's leading role in REDD+ forest protection, and 3) extremely low reported rates of forest clearance. The primary objectives of this study were to quantify the extent and total area of ASM, and to analyze and estimate the forest loss caused by these activities from 1986-2011. The changes in artisanal gold mining activity over a 25-year time period were studied based on available and suitable Landsat data with acceptable low cloud cover and a RapidEye image of 2011 with 5m resolution. Maximum-Likelihood supervised classification and knowledge engineer classifier were applied to the Landsat images. Object-based image analysis was used to segment and classify the RapidEye image. Post-classification comparisons were performed to estimate the changes in landuse and landcover. Accuracy of the classified images of 2010 and 2011 was then assessed against the RapidEye. High-Resolution Global Maps of Forest Change was also used to verify forest changes between 2000 and 2010. The results indicate that deforestation from gold mining increased between 1986 and 2011. The findings also highlighted the advantage of using high-resolution images and object based image classification technique to obtain accurate estimates.

I certify that the Abstract is a correct representation of the content of this thesis.

Chair, Thesis Committee Date

ACKNOWLEDGEMENTS

First and foremost I would like to thank the Almighty God, for all his wonderful deeds throughout my life. I could never have done this without the strength and wisdom you gave me, God.

I would like to express my deepest appreciation to my committee chair, Dr. Leonhard Blesius whose continuous motivation, guidance and ideas helped me complete this work. I express my sincere thanks to my committee members, Drs. Xiao Hang Liu and Logan Hennessy for their helpful reviews and comments. Moreover, special thanks to Drs. Leonhard Blesius and Logan Hennessy for providing the photos and other materials used in this study.

This research was supported by a grant from the Facilitating Research and Creative Work at San Francisco State University.

I thank the faculty members of the Department of Geography for giving me access to the GIS and Remote Sensing lab.

Finally, I take this opportunity to record my sincere thanks to my parents, Abeba Kaffl and Semere Mengisteab, my siblings, uncle and friends for their unceasing love and support.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

1. INTRODUCTION

Globally vast tracts of forests are lost every year especially in developing countries of the tropics due to various human activities such as lumbering, farming, bush fires, surface mining and urbanization (Kusimi, 2008). One of these major landuse transitions is the expansion of mining sites by cutting down trees. In many instances the economic benefits of mining are considered more important than the presence of forest cover. If a potential mining site is located in a forested region, the initial exploration stage of that mining would certainly involve the clearance of forests from the area. This includes the clearance of trees for road construction and related infrastructure that would support the mining project. Although some may argue that the area of land involved in mining is quite small and is not seen as a major cause of primary deforestation (Chakravarty, et al., 2012), if it is not properly managed and controlled it can be very harmful and destructive to the environment. Moreover, in the region around mining sites, change and development often occur rapidly due to the extensive socioeconomic opportunities that mineral production brings to a region (Sonter, et al., 2013). This can pose serious environmental and social problems to the affected area.

In a broad sense, there are three types of mining. These are the industrial mining, medium-scale mining and artisanal small scale mining. The practice and level of environmental problems caused by these three types of mining differ in relation to their scale. Industrial mining is widely practiced in developed countries, whereas small scale artisanal mining is predominantly practiced in developing countries. The impacts of mining activities on deforestation and forest degradation are more common in developing countries. Many of these countries have only recently implemented national environmental legislation, and of the laws pertinent to mining, many often fail to effectively regulate all aspects of the industry (Hilson, 2002).

In the Philippines for instance, mining, along with logging, has been among the forces behind the country's loss of forest cover: from 17 million hectares in 1934 to 3 million hectares in 2003, which is an 82% decline (Docena, 2010). In some countries like Peru, miners use explosive devices to clear large sections of forest. Such techniques have been used extensively in the Madre de Dios region, where some 7,000 hectares of forests and wetlands were cleared by miners between 2003 and 2009 (Swenson, et al., 2011).

Artisanal and small scale mining (ASM) can be defined as a low-tech, low-mechanized mining operations with predominantly manual (artisanal) work (Hruschka & Echavarria, 2011). Artisanal small scale mining sites are different from middle sized and large scale mining activities because of their small and compact area of average 27.5 acres. Small scale mining is accomplished in different ways. Land dredging and river dredging are two common methods. Land dredging is essentially the expansion of mining sites by cutting down trees and digging pits. River dredging on the other hand is the suctioning of alluvial sediments from river beds.

Figure 1: Aerial photo of a mining site in Upper Mazaruni River Basin (source: Hennessy and Blesius)

ASM is not a new phenomenon and many of the now developed countries have gone through the stage of mineral production from artisanal small scale miners at some time in their history. Today, ASM occurs in approximately 80 countries and there are roughly 100 million artisanal miners engaged in the sector globally (World Bank, 2013). Despite the long-history of ASM, there has been a significant increase in the volume of production and amount of capital invested in the last few decades. Many of these countries have recognized ASM as a means to help fight poverty, increase foreign exchange earnings or reduce rural-to-urban migration. (ILO, 2003). Artisanal and small scale gold mining in particular has existed and been part of people's life for thousands of years. In terms of production volume, the most important periods in the history of ASM gold production are, the 19th century gold rushes from 1849 to 1929, and the modern ongoing gold rush – roughly 1970 to present (Persaud & Telmer, 2013).

However, the above benefits are not without consequences. If ASM is not properly regulated and controlled it can cause severe environmental, ecological, social and health problems to the land and the people who live near mining sites. Within the substantial literature on different problems associated with ASM (Drake et al. 2001; Hilson 2009; Gibb & O'Leary 2014), the environmental risks caused by the sector are relatively neglected, yet the consequences of ASM on the environment can be enormous. It is argued that the environmental costs of ASM are in general higher than those of other types of mining or ASM is dirtier per unit of output than medium-sized or large and modern mining operations (Hentschel, et al., 2003). Besides deforestation, other examples of the most common problems are land degradation, mercury pollution, river siltation and erosion.

In Guyana, different studies indicate that there has been an expansion of small scale mining sites in recent decades. It is estimated that there are between 10,000 to 12,000 artisanal small scale miners in the country (Lowe, 2005). However, the growth of ASM in Guyana has received little attention in the literature, despite its rapid growth and being of central importance to the country's socioeconomic status (Clifford, 2011). Both forms of ASM which are the land dredging and river dredging are mostly exercised in the thick Amazon forest along rivers and streams. An example of land and river dredging is shown in figure 2:

Figure 2: Land dredging and river dredging in the study area (source: Hennessy and Blesius)

Forest conservation is very critical in Guyana, mainly after the signing of the Reduced Emissions from Deforestation and Forest Degradation (REDD+) Memorandum with the Norwegian government in 2009. This essentially commits both governments to an inclusive policy making process in all activities related to forest and climate protection (Dooley & Griffiths, 2014). However, according to the Guyanese Ministry of Natural Resources and Environment, mining is the main driver of forest change in Guyana (MNRE, 2013). Mining activities are at the forefront of causing serious impacts on the surrounding environment such as: river and land pollution, erosion, forest loss, ecological disturbance and other related problems. The deforestation rate due to mining activities from 2000 to 2008 increased by 2.77 times according to an assessment by the World Wildlife Fund-Guianas (Staff, 2010). In 2012 alone, 92% or 13,516 hectares of the total deforestation in the country was caused by small scale mining activities (MNRE, 2013). Estimating and monitoring these losses on a regular basis is one step towards controlling the damages. However, acquiring the necessary data is not always simple. Natural and man-made hindrances are very common issues associated to getting data from the ground. Geographic Information Science (GIS) and Remote Sensing (RS) tools and techniques play major roles in solving this limitation. Remote sensing in particular plays a significant role in mine monitoring to sustain safe and effective operations and mitigate the risks associated with them (Düzgün & Demirel, 2011). Remote sensing in the form of satellite images in particular provides a great range of spatial and temporal information that can be used to analyze, quantify or monitor land cover transformation from forest cover to sites of small scale mining.

Furthermore, the acquired images need to be processed appropriately in order to convey the most accurate estimate of the forest loss caused by ASM. Two of the commonly used approaches to analyze satellite images are the traditional pixel-based and the more recent object-based image analysis (OBIA) processing strategies.

The pixel-based approach which was developed in the 1970's, makes use of spectral information of the pixels to classify the image into different classes. However, the fact that only the spectral information of an image is considered is a major drawback of the approach.

In Object-based image classification approach, image objects are generated and classified according to their physical (color and texture), spatial (location, shape, neighborhood, distances etc.) and scale (structures and embedding) properties (Marschallinger and Hofmann 2010). The two main stages in OBIA are segmentation and classification. Segmentation is the clustering or grouping of pixels into meaningful areas. Expert knowledge is essential in the segmentation stage. Segmentation is done in numerous scales in order to allow the differentiation of object categories into various levels. Only good segmentation results can lead to object-oriented image classification out-performing pixel-based classification (Gao, et al., 2006). Classification in OBIA is done by the formation of classes based on rulesets. According to the user's ruleset, the segmented objects of the image are clustered together to form homogenous classes.

The Object Oriented Image Classification approach is an effective way of classifying satellite images. Many comparative studies of pixel-based and object oriented image classification techniques have shown that an object-based approach provides better results than traditional image processing techniques (Sarmadian, et al., 2007; Myint, et al., 2011). However, OBIA requires high user interaction in selecting appropriate parameters for example to perform segmentation.

Numerous studies have demonstrated the application of remote sensing data acquired at different observation scales for monitoring mining activities and their implications on the environment. For instance, Ieronimidi, et al. (2006) used different image fusion techniques on QuickBird images to maximize spectral and spatial resolution of the original image for studying mined areas. Pagot, et al. (2008) applied an object-oriented, maximum likelihood classification scheme to process bi-temporal IKONOS images of diamond mines in west-Africa.

Therefore, this study builds on previous research by examining the effectiveness of both pixel-based and OBIA in classifying small scale mining sites from Landsat and RapidEye satellite images. The final results from these analyses are intended to demonstrate the patterns of ASM in quantitative and spatial forms.

The main goal of this research paper is to detect, quantify and analyze the state of ASM in the Jawalla village area in Upper Mazaruni River Basin located in western Guyana. In order to achieve this aim, multi-temporal Landsat images and a high resolution RapidEye image were used as primary sources. Pixel-based and object based image analyses approaches were then applied to the images. The pixel-based image processing solely focused on the Landsat images of 30 meter resolution. Initially 45 Landsat images were considered between the years 1986-2011. However, only the images from 1986, 1999 and 2010 that had relatively low cloud cover were selected for further processing. Geometric and atmospheric corrections were performed in Erdas Imagine 2013 and Atcor 2. Then both maximum-likelihood supervised classification and Knowledge Engineer Classifier were implemented to attain the final results. On the other hand, object-based image analysis (OBIA) approach was mainly focused on the RapidEye image from 2011 that had a resolution of 5m.

The specific research goals of this study are, by developing robust image processing approaches to:

1. Classify the study area into different landuse and landcover (LULC) categories

2. Quantify the extent and total area of ASM in forests and rivers

3. Analyze the extent of forest loss and river sedimentation over the study period

The research study was based on the premise that ASM has been increasing in the Upper Mazaruni River basin in the last three decades causing deforestation and high sedimentation in rivers. The study closely examines two major assumptions:

1. Pixel-based and OBIA can be used to quantify the extent of forest loss from ASM.

2. OBIA can be more effective than pixel-based in distinguishing different levels of ASM activities.

2. STUDY AREA

2.1 General Description of Study Site

Guyana is a small country located at the north east coast of South America and has a population of about 750,000. Eighty percent of its 214, 969 square km total area is covered with forests. The major types of forests in Guyana are rainforest, seasonal forest, dry evergreen forest, marsh forest and mountain forest (ITTO, 2011).

Of the many rivers and streams in the Guyana, the Mazaruni River which is an important source of alluvial gold and diamond, is a tributary of the Essequibo River and has a length of 560 km (The Columbia Encyclopedia, 6th ed., 2014). The Mazaruni River together with the Cuyuni and Potaro rivers account for 80% of ASM activities (Hennessy, 2014).

This research is focused around the Jawalla village of the Upper Mazaruni River Basin which is located in the western-part of Guyana (figure 3). The total area of this study area is approximately 361 square km extending from 5°46’N to 5°38’N and 60°35’W to 60°20’W. This region is predominantly covered by montane forests and upland shrub savanna (Huber, et al., 1995). The Upper Mazaruni River Basin which borders Venezuela and Brazil is part of the Guyana Shield which is known to be one of the ancient and most vulnerable ecosystems in the world (George & Almås, 2015).

The Amerindians are the very first settlers of Guyana and they account for 7% to 8% of the total population in the county (IHRC, 2007). The Upper Mazaruni River Basin region is the home of the Akawaio tribe. Although there is no reliable census, it is estimated that there were about 6000 Akawaio in the Upper Mazaruni River Basin and nearby areas (Colson, 1996). The Upper Mazaruni District was formally created as an Amerindian district in 1945, twenty one years before the independence of Guyana from Britain (Brosius, et al., 2005). The region is extensively covered by rainforests. Artisanal small scale gold mining is a significant activity in the area. There are about 12,000 persons, mostly Amerindians that are directly engaged in the sector in the interior parts of Guyana including the Upper Mazaruni River Basin (Colchester, et al., 2002).

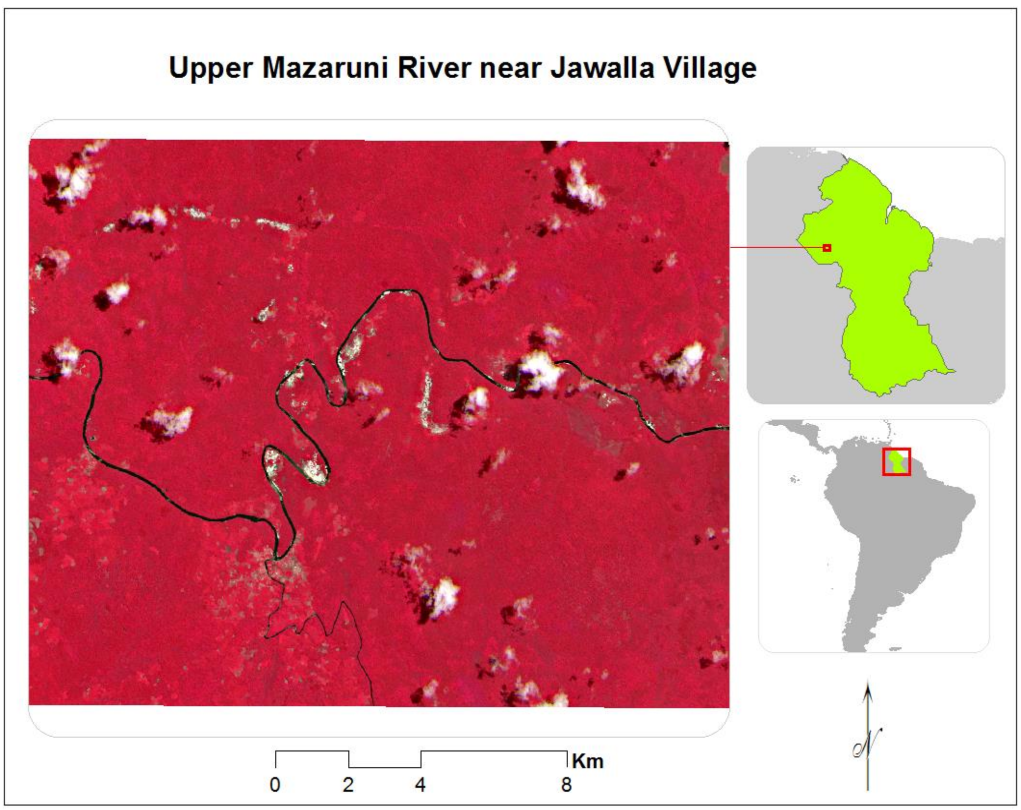


Figure 3: Overview of study area with location inset (satellite image shown is the 2011 RapidEye image)

2.2 Historical Background of Small Scale Gold Mining in Guyana

Gold mining has a long history in Guyana. According to Brosius et al. (2005), the first concerted attempt to mine gold was carried out on the Mazaruni in 1863 and 1864. Production was estimated to be 40 ounces in 1882, but thirty years later reached 138,000 ounces. The activity therefore became a lucrative option to retreat from working in plantations. However, a decline in production was registered once the easiest deposits were taken out (Brosius, et al., 2005).

According to Clifford (2011), small scale gold production has been increasing steadily since 1970's. This was caused by the increase in global gold prices and decline in socio-economic conditions in the country. Figure 4 shows the increasing trend of gold production since 1979.

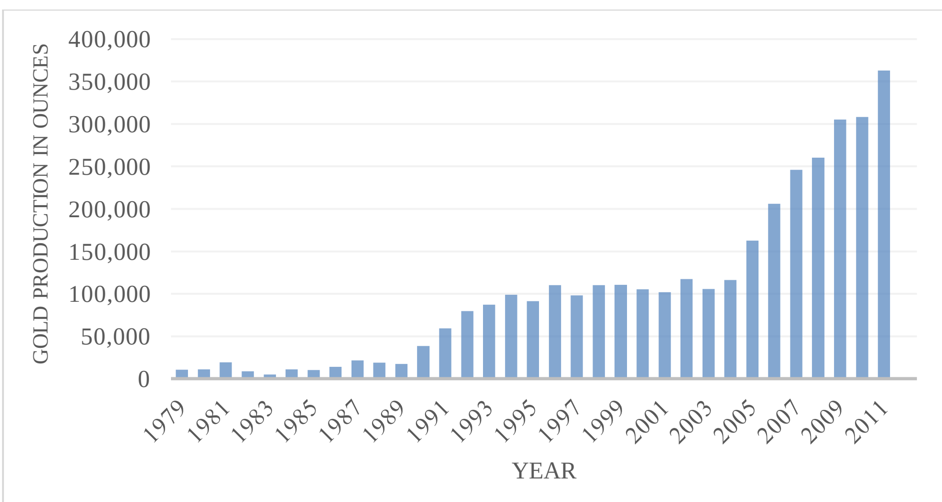


Figure 4: Guyana gold production 1979–2011 (Guyana Geology and Mines Commission, 2011)

Amerindian communities and the government of Guyana have had numerous disagreements over titling of lands. Amerindian peoples have been demanding full control of their lands and all activities done there, including mining. However, the 1989 Guyana Mining Act highlighted that all minerals within the lands of the Guyana shall be under the control of the State (Ministry of Legal Affairs , 1989). Hence, the government of Guyana expanded state-sponsored mining developments particularly after designating 6 mining districts in the country which included the Upper Mazaruni River Basin. The government also allowed foreign mining companies to conduct exploratory study in the region and allowed small scale mining (Brosius, et al., 2005).

Amerindian communities felt neglected and blamed the government for lack of transparency, despite the government's policy to involve them in decisions about mining in their lands (Colchester, et al., 2002). They argue that because of mining activities, many of which were permitted to foreigners and coastal persons, they continually suffer from environmental and social consequences.

More than 90% of Amerindians live under the poverty line and they suffer from different sorts of social problems caused by small scale mining that mostly take place in interior lands where they live. Some of the social effects are the rise in crime, prostitution, rapid spread of social diseases, and disruption of their traditional life-style (IHRC, 2007; Thomas, 2009). Most of the rivers where they depend on for drinking, bathing and fishing are contaminated because the miners dispose their waste into the river.

Although, the Guyanese government signed a UN declaration in 2007 that allowed indigenous peoples to have the right to the lands, territories and resources which they have traditionally owned, occupied or otherwise used or acquired (Colchester and La Rose, 2010), there has been little change on the ground according to the Amerindians.

2.3 Mining and Deforestation

Generally the rate of deforestation in Guyana is very low when compared to other countries. The government of Guyana continuously rejects claims of an increase in mining activity in Guyana, leading to an increase in deforestation (Guyana Times, 2013). However, different studies argue otherwise. Studies have shown that gold-mining is a significant cause of forest degradation and environmental pollution in the country (ITTO, 2011). Between 2010 and 2011 94% of identified deforestation was caused from mining (Conservation International, et al., 2013).

Mining in the Upper Mazaruni is responsible for extensive deforestation, land degradation (figure 2) and damage to water resources according to George & Almås (2014). Forest loss and expansion of small scale mining activities have been increasing in this part of the country. Annual deforestation attributable to mining and related infrastructure has increased from over 1,000 ha per year between 1990 and 2000 to nearly 10,000 ha in 2010, before falling slightly to 7,000 ha in 2011 (Conservation International, et al., 2013). Evidently a team of researchers that flew over the region in 2005 observed extensive deforested scars dotting the rainforest that signify small scale mining sites (International Human Rights Clinic, 2007). Figure 1 shows this to be still the case in 2014.

On the other hand, Guyana's involvement in Reduced Emissions from Deforestation and Degradation (REDD+) have enabled the country get financial assistance from Norway, while forcing the government to quantify and reduce impacts of mining (Hennessy, 2014). However, the build-up to and launch of Low Carbon Development Strategy (LCDS) and REDD+, has caused clashes between government authorities and miners, because the small scale miners see this strategy as a threat to their livelihood (Clifford 2011; Dow et al., 2009).

3. METHODOLOGY

3.1 Data and Tools Used

This study in general and the processing stage in particular focused on 30m Landsat and 5m RapidEye images. Two types of image classification approaches were used to create final results. The workflows for the pixel-based and object-based classification approaches are displayed in figures 5 and 6 respectively.

As mentioned before, a total of 45 Landsat satellite images were evaluated and 3 images from 1986, 1999 and 2011 with minimum cloud cover were selected for further analysis. After geometric and atmospheric corrections were applied, maximum-likelihood classifier method was used for supervised classification. In an effort to further improve results, knowledge engineer classification technique was performed.

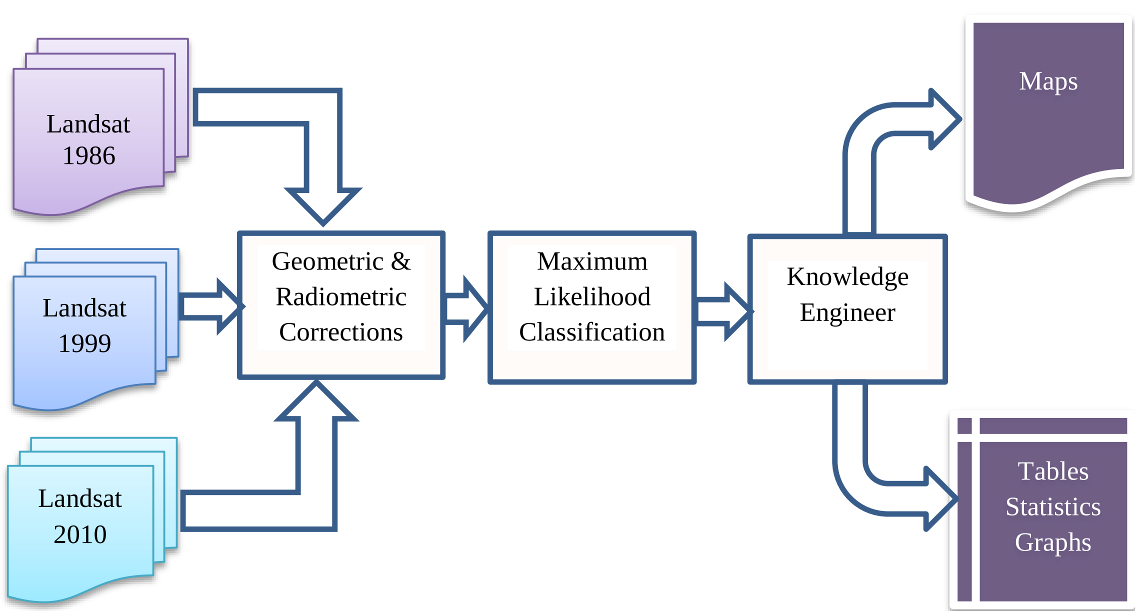


Figure 5: Pixel-based classification workflow

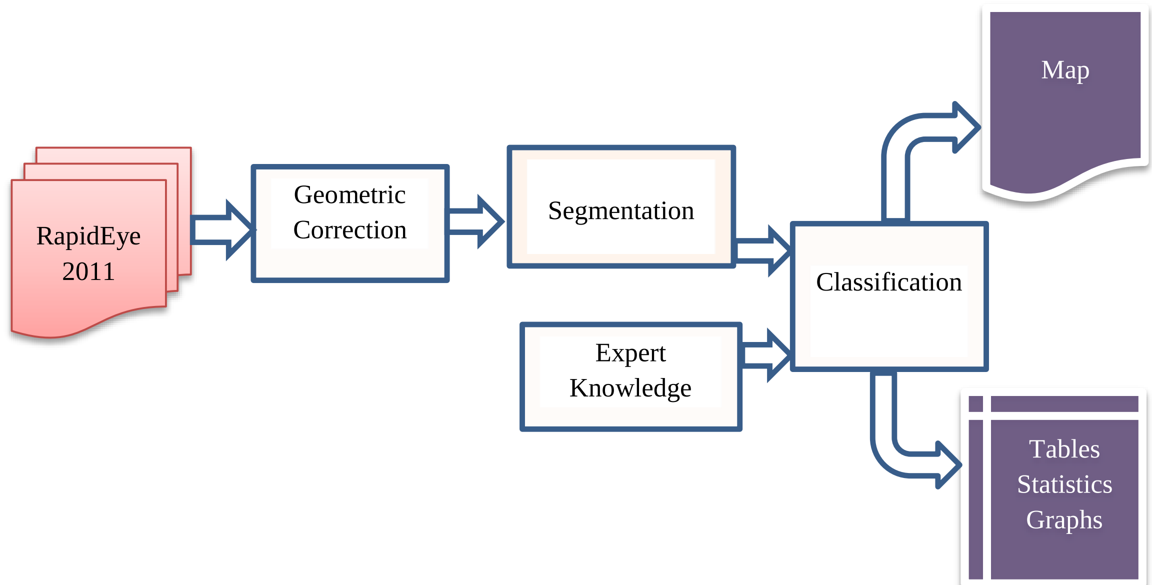


Figure 6: Object-based classification workflow

In order to minimize the effects of solar illumination and related factors, all the images were acquired from the same season. The months of acquisition were October, November and December for the Landsat TM images of 1986, 1999 and 2010 respectively. The RapidEye image which had 5 spectral bands, was acquired in September 2011.

In almost all the images cloud cover was inevitable, mainly due to the geographical location of Guyana. The list of satellite images used in this study is listed below:

Table 1: List of images used in the study

Satellite	Spectral Bands	Pixel size	Acquisition Time
Landsat 5	7 bands	30 Meter	10/04/1986
Landsat 7	7 bands	30 Meter	11/17/1999
Landsat 5	7 bands	30 Meter	12/09/2010
RapidEye	5 bands	5 meter	08/09/2011

Several software packages were used to conduct this study. Erdas Imagine 2013 and Atcor 2 were used to perform geometric and atmospheric corrections as well as pixel-based classification. ArcGIS 10.2 was used to create a thematic layer that masks out cloud cover in the RapidEye image. Finally, eCogntion was used to accomplish segmentation, extraction of image information and object- based classification of the RapidEye image.

The RapidEye image used for this study needed to be georeferenced and it was re corrected using image to image registration with reference to the Landsat images. This correction was completed using nearest neighbor resampling technique in Erdas Imagine 2013. Atmospheric Correction was applied to correct the atmospheric distortions of a satellite image related to haze, sun angle and skylight, which can be important factors in multi-temporal analysis. Although, the inclusion of Digital Elevation Model (DEM) in Atcor 3 of Erdas Imagine significantly increases the quality of the atmospheric correction, due to the lack of high resolution DEM of the study area, instead the Atcor 2 workstation of Erdas Imagine 2013 was used.

Finally in the pre-processing stage, a thematic vector map that masked out clouds in the RapidEye image was created. The main use of this thematic map for clouds was to avoid misclassification with bright white mining sites. Pagot et. al., (2008) also applied the same technique to prevent misclassification of built-up areas, roads and industrial dykes from excavation materials and mining pits.

3.2 Classification of Landsat Images

The traditional maximum-likelihood classification was applied, as it is still the most widely used technique. Training areas were selected using the high-resolution RapidEye image as a reference, because field surveys could not be conducted. A total of 8 landuse /landcover (LULC) classes were considered. The list of the classes are: Sedimented pits, mining sites, river sediments, river, grassland, forest, cloud and shadows.

This initial classification was followed by the Knowledge Engineer application in order to attain better results. The main use of knowledge engineer is that users can develop methodology, define variables, set rules and design a hierarchical decision tree (Jensen, et al., 2007). In addition to the spectral bands of the images, other indicators such as NDVI (Normalized Difference Vegetation Index) and the result of the supervised classification image were also incorporated to set rules of classification for separation between classes.

3.3 Classification of RapidEye Image

The procedures of segmentation and classification for the RapidEye image were performed in eCognition 9.0.1. This is a software used for object based image analysis. For high resolution image such as RapidEye, it may be a better choice for detection of mining pits which normally are small in size.

The RapidEye image and the thematic map of the cloud mask were loaded as image layers into eCognition. The Near Infrared Red (band 5) layer was given a slightly higher layer weight than the other layers. Scale values for segmentation were set at different levels (for example scale of 20 for mining pits and scale of greater than 200 for vegetation). These levels were set according to the size of the objects of interest.

The shape and color factors were very essential in spotting the mining sites. The difference in color implies the different levels and stages of a mining activity. For instance, an orange or yellow color in a river signifies a mining activity, while a dark and translucent color means the river is undisturbed. The RapidEye image clearly shows potential mining pits with distinct color and usually a round shape. Therefore, based on the visual interpretation of the images, the shape/color values were given equal weights, as both factors were essential in identifying the objects of interest.

After the above parameters were set, the image was segmented using the multi-resolution segmentation technique (figure 7). Spectral difference segmentation was later applied to merge neighboring objects according to their mean layer intensity values.

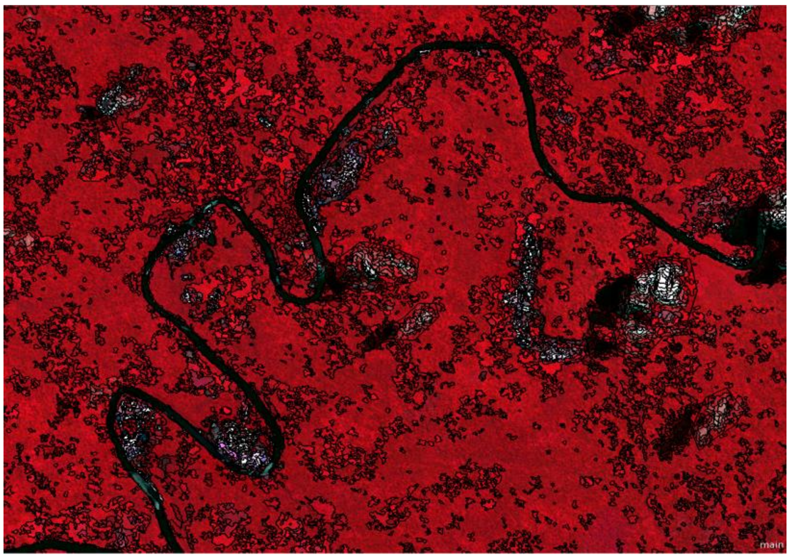
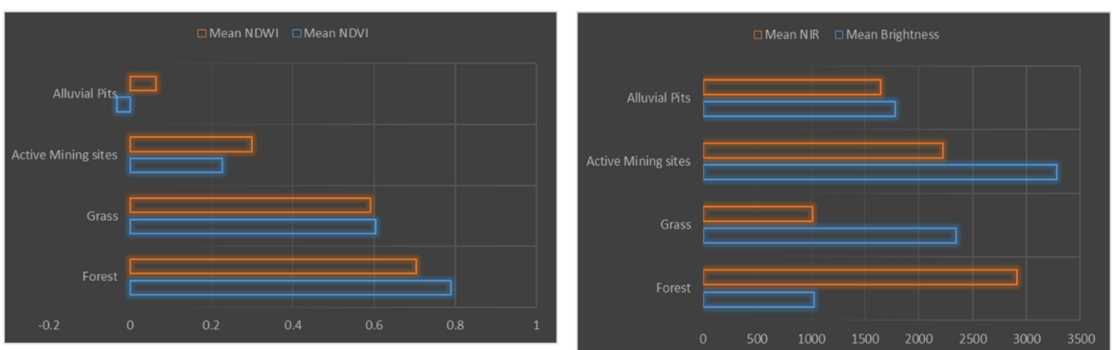


Figure 7: The segmented RapidEye image

In the classification stage, the classes were created in relation to the supervised and knowledge engineer classification results so that they can be compared. Therefore, a hierarchy of a classification tree was established in eCognition. Various indicators or factors were used to classify all the classes (see example in figure 8). More emphasis was given to alluvial pits, mining sites and river sediments, because these classes were assumed to have direct relation with artisanal small scale gold mining activities in the region. Classification explicitly incorporated numerous scales in order to accommodate different real-world objects. Arithmetic variables such as NDVI and NDWI, and spatial relationships such as Euclidian distance between features were also taken into consideration.



Average NDWI and NDVI values of selected classes

Average NIR and Brightness values of selected classes

Figure 8: Some of the indicators used to separate classes

Accordingly, the following classes were formed:

i. Forest: This class was the most dominant one. Despite the fact that different sub classes of various tree types could have been extracted, for the sake of simplification all different vegetation types in the study area were generalized in one class, because tree species classification was not the focus of the investigation. Normalized Difference Vegetation Index (NDVI) was used as an important distinctive element in differentiating the vegetated and non-vegetated areas. All features with NDVI values of 0.7 or higher were categorized in this class.

ii. *Grassland:* had similar characteristics to the forest. But the NDVI value of 0.4 to 0.7 was used to differentiate it from the forest class.

iii. Barren land: initially constituted all the unclassified (non-vegetated) areas that do not belong to forests and grasslands. It served as a base of classification for the rest of the classes except for the river class, until it finally formed a class.

iv. *River*: The Near Infrared (NIR) band and brightness values of the image were used in clarifying the river from other features. These two alone were not absolutely sufficient. Therefore, new sub-class (river edge) that was formed using other indicators, was used before merging it back to the main river class.

v. River sediments: The Normalized Difference Water Index (NDWI) was appropriate factor to delineate this class. Non-vegetated objects with NDWI value of 0.423 or less with a limited distance to the river were categorized as River Sediments class.

v. Clouds and Cloud shadows: were masked out using the thematic image created in ArcGIS. There were some leftover shadows which were later separated from similar features using NDVI and “border to” classification rules.

vi*. *Mining sites: are clusters of tiny pits which can be recognized on the image by their high brightness and texture. Some pits can be filled with water, however the presence of the dry pits which signify high mining intensity, is the key identifying factor. This class was very essential to clearly delineate, as it was one of the three classes of interest for this study. Therefore objects with brightness values of 1618 or more with close distance to the river class were grouped in to this class. This brightness level considered all the bands.

vii. Alluvial Pits: are characterized by pits filled with water. They are round in shape and are located with close proximity of the river class. The presence or absence of water, sediments and excavated materials were used as classification indicators for (Pagot, et al., 2008) in their research to detect diamond pits. For this project, these indicators were taken into account in addition to the unique blue color of the alluvial pits which could be visually detected. Then objects with HIS Transformation (Hue, Intensity and Saturation) Hue value between 0.72 and 0.91 of the Green, Blue and NIR bands were categorized as alluvial pits. These values were obtained after several trial and error adjustments of the HIS levels.

viii. Sedimented Pits: are usually isolated and individual pits characterized by their dryness and moderate level of brightness. They signify high level of activity. Spatial variables (such as relative distance to a river) were mostly applied to detect this class.

ix. Built-up (Settlements): included both residential areas and farm lands. Spatial relationships (e.g. their spatial location) and brightness values were used to form this class. The final classification scheme is displayed in figure 9.

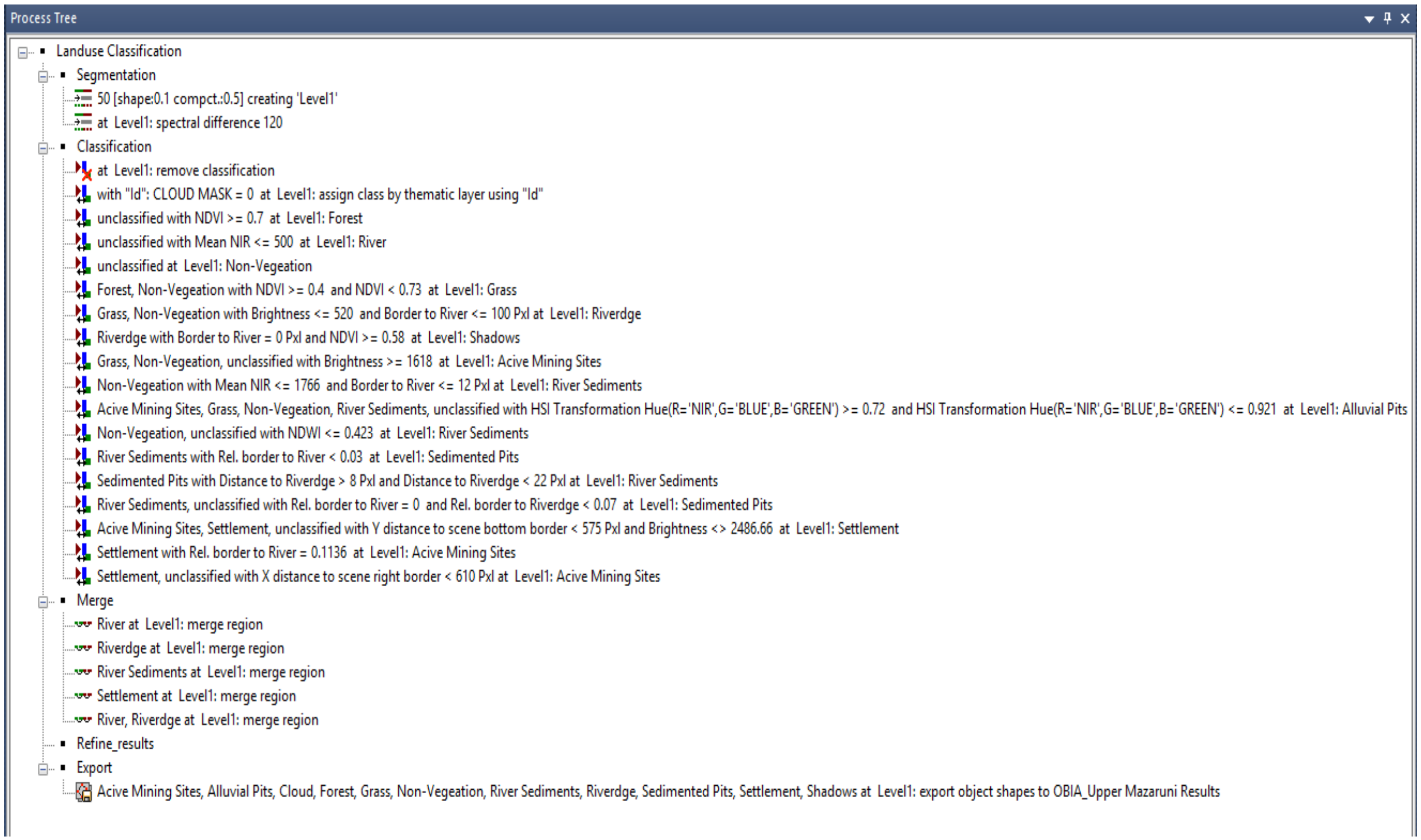


Figure 9: OBIA classification scheme

4. RESULTS

4.1 Interpretation of LULC Obtained from Landsat

The results of the landuse/landcover (LULC) classification are presented in tables 2 and 3 as well as figure 10..Table 2 displays the changes of LULC between the years of 1986, 1999 and 2010 in square kilometers which were obtained from Landsat images, while table 3 shows the results of classification acquired from the RapidEye image.

It is also important to point out that the presence of clouds and shadows had impacted the total area of several classes. In order to observe the results of the areas that were not affected by clouds in all the 4 images, section 5 of this research evaluates the results in a form of a graph (figure 14) and descriptive statistics.

Table 2: Classification results of LULC 1986, 1999 and 2010

	Landsat Images		
	1986	1999	2010
Landuse/Landcover	Area in Square km	Area in Square km	Area in Square km
Sedimented Pits	0.26	0.57	0.75
Mining Sites	0.70	0.70	0.65
River sediments	0.16	1.09	1.94
River	2.82	2.46	3.8
Grassland	7.7	6.76	2.75
Forest	343.95	349.42	328.70
Cloud	4.69	0.16	14.87
Shadow	1.94	0.83	8.37
Total	361.8	361.8	361.8

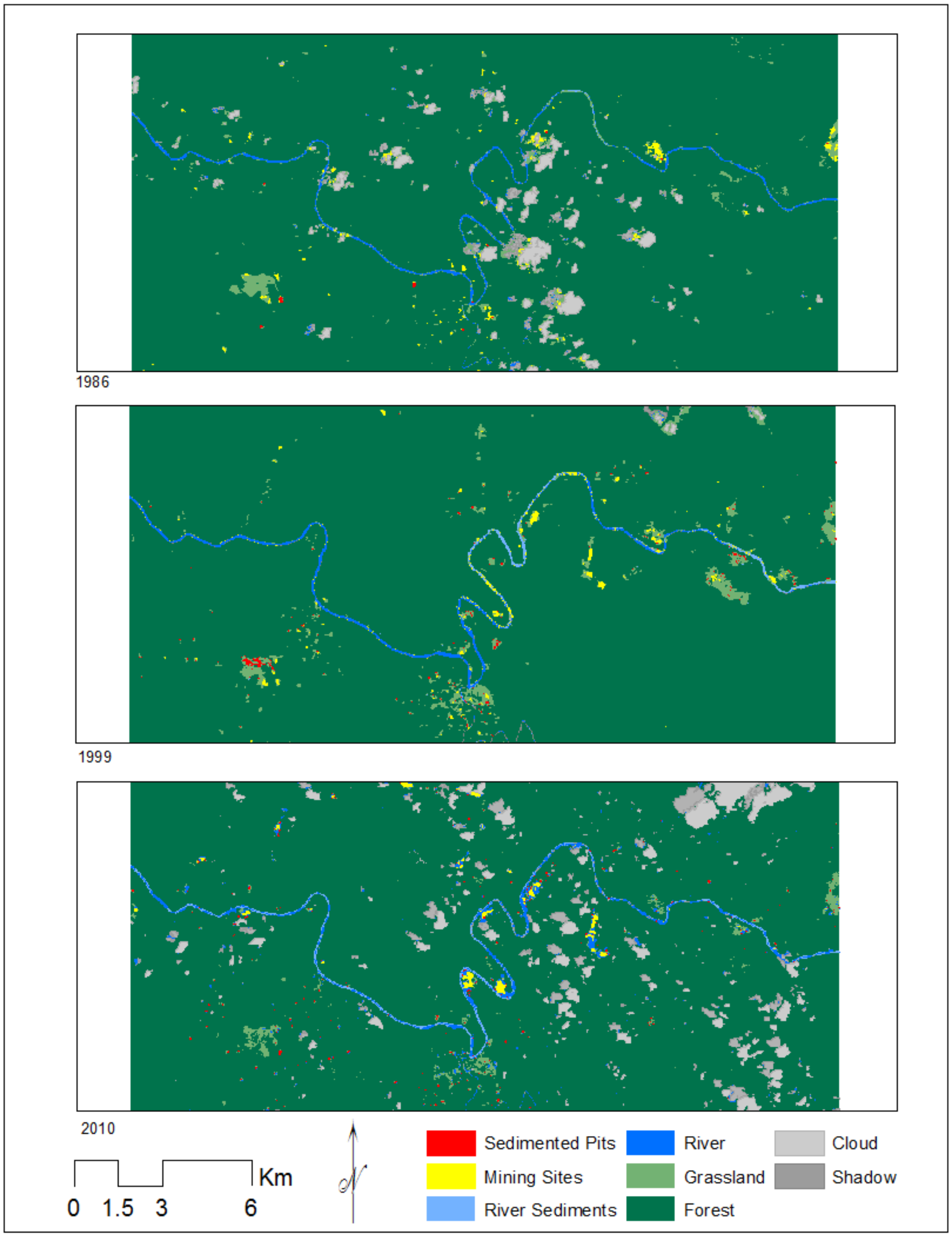


Figure 10: LULC maps of 1986, 1999 and 2010

Out of the eight classes, the three main categories that directly imply mining activities were, the sedimented pits (small, bright and isolated mining spots), mining sites (the clusters of dry pits characterized by their bright surface) and river sediments (parts of the main river that signify sedimentation).

The classification results show that there was an increase of 188% in the total area of the sedimented pits class from 0.26 square km in 1986 to 0.75 square km in 2010. The rate of increase was higher from 1986-1999 (0.31 square km) than from 1999-2010 (0.18 square km). On the other hand, the mining sites class registered no change between 1986 and 1999 with 0.7 square km. From 1999 to 2010 the total area of these sites declined by 7% to 0.65 square km. However, visual interpretation of the Landsat 2010 showed that significant portions of the mining sites class were blocked by clouds and shadows.

The class that showed substantial changes over the 24 years period was the River sediments class. This class went up from 0.16 square km in 1986 to 1.09 square km in 1999 and then to 1.94 square km in 2010. High sedimentation was mostly notable in areas where mining sites were in close proximity to the main river. This is reasonable given the mining site development.

Another significant change that can be observed from the results is the decline in vegetation cover. The grassland area slowly declined by 12% from 7.7 square km in 1986 to 6.76 square km in 1999. The decline continued to 2.75 square km in 2010. Based on these findings, grassland cover fell by 64% from 1986 to 2010. The reason for this could be that the area classified as grassland in some Indian lands could have been crop lands, and with the shift from agriculture to gold mining, the class may have shrunk. Recently, the abandonment of agriculture for gold mining has been recognized as a major problem in Guyana (Guyana Times, 2014).

The forest class is the largest LULC class in the classification. In 1986, this class had covered 343.95 square km of the study area, excluding the areas covered by significant clouds. After 13 years, the total area it accounted grew to 349.42 square km, registering 1.6% increase. The total area of this class plummeted by 6% to 328.70 square km in 2010. However, as can be visually interpreted from the 1986 and 2010 images in figure 2, majority of the cloud and shadow classes fell on forest covers. On the contrary, the 1999 image has the lowest cloud and shadow cover. Therefore it is assumed that, the total area of the forest class in 1986 might have been larger than 343.95 square km.

4.2 Interpretation of LULC Obtained from RapidEye

The RapidEye image of 5m was processed and classified in eCognition using the object based image classification technique (figure 11). A total of 11 classes were created. Alluvial pits, settlement and barren land classes were the three additional classes. The high resolution of the image and the robust nature of OBIA in separating similar classes were the two main reasons for the addition of these classes. Table 3 presents the descriptive results of the LULC of the classified map.

Table 3: Classification results of LULC 2011

Landcover/Landuse	**Area in Square km**
Alluvial Pits	0.06
Sedimented Pits	0.44
Mining Sites	1.4
River sediments	0.44
River	3.34
Settlement	0.10
Barren Land	0.36
Grassland	6.2
Forest	330.8
Cloud	18.9
Shadows	0.06
Total	**361.8**

As it was mentioned in the previous chapter, clouds were masked out to avoid misclassification with mining sites class. They stood out as the second largest class next to forest class by covering 5.2% of the study area.

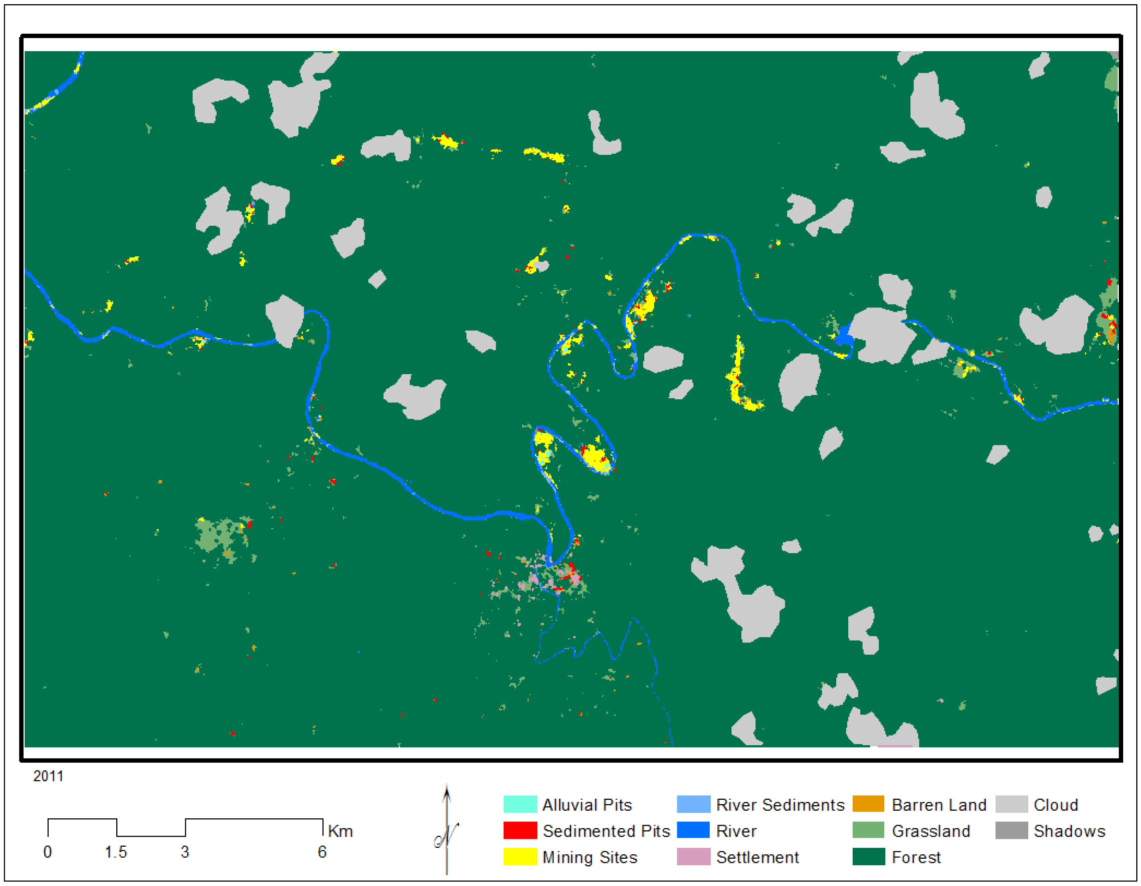


Figure 11: LULC map of 2011

4.3 Accuracy Assessment Results

For this study, the RapidEye image of 5m resolution and a High-Resolution Global Maps of Forest Change which was developed by quantifying forest change between 2000-2010 (Hansen, et al., 2013) were used as reference data for accuracy assessment. Despite the fact that field observations undoubtedly offer reliable information for accuracy assessment, collection of ground points was not possible for this study. Two members of the research team for this study who flew to Guyana to collect data were not able to do that, due to collection restrictions sanctioned by the authorities in Guyana. The very few ground control points (majority of them in river banks) they were permitted to collect were unfortunately insufficient to make any conclusions.

Accuracy assessment could not be done for the LULC of 1986 and 1999 since there were no any reliable maps or supplemental information that could serve as reference. Hence, the accuracy assessment was focused on the LULC of the 2010 (classified using pixel-based) and the LULC of 2011 (classified using OBIA), because of the smaller time difference.

4.3.1 Sample Sizes

For this study, the number of samples was determined using the following Worst-case scenario formula adopted from (Congalton & Green, 2009):

$$n=B/4b^2$$

Where:

n = total samples of all classes

B = the upper (α/k) x 100th percentile of the Chi-Squared distribution with 1 degree of freedom

b = significance level

B was 6.24 and 6.6 for the 2010 and 2011 images respectively. Moreover, a 90% significance level was used for both images.

Thus, 160 samples for the 2010 and 155 samples for the 2011 images were determined. Next, the selection of proper sampling scheme is significant in obtaining an error matrix that is representative of the entire classified image (Luneta, et al., 1991). Stratified random distribution technique was used to allocate the samples to all classes.

4.3.2 Descriptive Analysis of Accuracy Assessment Results

Error matrix is a widely used form of representing accuracy results. Erdas Imagine 2013 was the software used for accuracy assessment. The overall accuracy, kappa statistic and user's and producer's accuracy were accomplished for the LULC maps of 2010 and 2011. The Kappa statistic is an alternative measure of classification accuracy that quantifies how much better a particular classification is in comparison with a random classification (Giri, 2012).

In table 4, the LULC 2010 which was derived using supervised classification and knowledge engineer, registered an overall accuracy of 70%. In table 5, the overall accuracy of the LULC 2011 which was derived using OBIA was 83.2%.

The Producer's accuracy indicates the probability of a reference pixel being correctly classified and the user's accuracy refers to the probability that a pixel classified on the map represents that category on the ground (Congalton, 1991). For the LULC 2010, the user's and producer's accuracy results were between 22.2% - 100% and 32%-100% respectively. The highest user's accuracy was registered for the forest class. Whereas Sedimented Pits and River classes had the lowest user's accuracy. This could be due to similarities of spectral properties with grassland and river sediments. Similarly, forest class attributed the highest producer's accuracy, while the river class recorded the lowest producer's accuracy: This was mainly because of the misclassification of some parts of the river as river sediments.

The image classified using OBIA attributed higher producers and users accuracies when compared to the LULC of 2010. The user's accuracy was in the range of 50%-100% while the producer's accuracy ranged from 67%- 100%. The classes with highest user's accuracy were forest and mining sites, while grassland and sedimented pits resulted in low user's accuracy. The reason for this could be misclassification caused by similarities of spectral signature with other classes such as settlement and barren land. On the other hand river sediments and river classes recorded the highest producer's accuracy, whereas mining sites and grassland classes attributed lower producer's accuracy with 67.7% and 70% respectively.

Another way to assess classification accuracy is kappa coefficient. It expresses the proportionate reduction in error generated by a classification process compared with the error of a completely random classification (Whitaker & Amlaner, 2012). The LULC of 2010 attained an overall Kappa Statistic of 66%. While the LULC of 2011 registered an overall Kappa statistic of 82%.

Finally, the High-Resolution Global Maps of Forest Change was used to assess the difference in vegetation between the years of 1999-2010. This was aimed at inquiring if the forest class of 2010 was correctly classified to represent the state of forest cover in the Global Maps of Forest Change. For this purpose, an accuracy assessment that only focused on the forest class was accomplished. A total of 58 reference samples were used to conduct the accuracy assessment. The users and producers accuracy were 94% and 86% respectively. The kappa statistic was 92%. Based on these findings, it can be inferred that the forest cover in the LULC 2010 was consistent with the results acquired by the High-Resolution Global Maps of Forest Change (Hansen, et al., 2013).

Table 4: Accuracy Assessment Results of LULC 2010

Classified Data	**Reference Data**							
	Grassland	Mining sites	Sedimented Pits	Forest	River	River Sediments	Cloud	Shadow
Grassland	**17**	2		1				
Mining sites		**18**			2			
Sedimented Pits	10	2	**4**	1		1		
Forest				**20**				
River	1	5	2	1	**7**	2		
River Sediments					13	**7**		
Cloud				1			**19**	
Shadow								**20**
Producers Accuracy (%)	61	67	67	77	32	70	100	91
Users Accuracy (%)	85	90	22	100	35	35	95	100
Kappa Statistic (%)	82	88	19	100	25	31	94	100

Totals	
Overall Classification Accuracy	**70.00%**
Overall Kappa Statistics	**65.7%**

Table 5: Accuracy Assessment Results of LULC 2011

		Reference Data									
		River Sediments	Grassland	Sedimented Pits	Mining sites	Alluvial Pits	Shadow	Barren Land	Forest	River	Settlement
Classified Data	River Sediments	**12**			2						
	Grassland		**7**		2			1	1	1	2
	Sedimented Pits		1	**8**	1	1		4			
	Mining sites				**14**						
	Alluvial Pits			2	1	**11**					
	Shadow						**14**				
	Barren Land				1			**12**	1		
	Forest								**14**		
	River	1					1			**12**	
	Settlement		2								**12**
	Producers Accuracy (%)	92	70	80	67	92	93	71	82	92	86
	Users Accuracy (%)	86	50	57	100	79	100	86	100	86	86
	Kappa Statistic (%)	84	47	54	100	77	100	84	100	84	84

Totals	
Overall Classification Accuracy	**83.23%**
Overall Kappa Statistics	**81.6%**

5. DISCUSSIONS

In this study, the amount of cloud cover in each image was considerably different from another one. The classes affected by clouds were also not the same for each image. Thus, in order to minimize this issue, the clouds and shadows of all images were extracted and aggregated in ArcGIS to form a separate layer. Then this layer was overlayed on each image so that the effect of clouds and shadows remains the same for every image. Finally, from the 316 square km cloud free area, total area of each class was calculated and compared. Figure 14 shows the changes in total areas for mining, river sediments, forests and grasslands between 1986 and 2011. However, it should be noted that, this comparison might not represent the actual changes overtime, since many of the LULC changes might have taken in the cloud covered regions.

In figure 14:a, the classes that indicate mining activities (mining sites, sedimented pits and alluvial pits) were combined to show the trend of artisanal gold mining activities between 1986 and 2011. Between 1986 and 2011, the total area of mining activities increased by 77% from 0.96 square km to 1.7 square km. In a similar manner, there had been a steady increase in the level of sedimentation between 1986 (0.13 square km), 1999 (0.93 square km) and 2010 (1.76 square km). But this rate of increase was not demonstrated in the LULC 2011. The reason for this was that, substantial portions of the sediments class from the Landsat image of 2010 were actually detected as mining areas in the high resolution image of 2011. This type of mining activity that takes place in rivers is referred as river dredging. Separation of river dredging from river sediments using course resolution images is therefore, a difficult task.

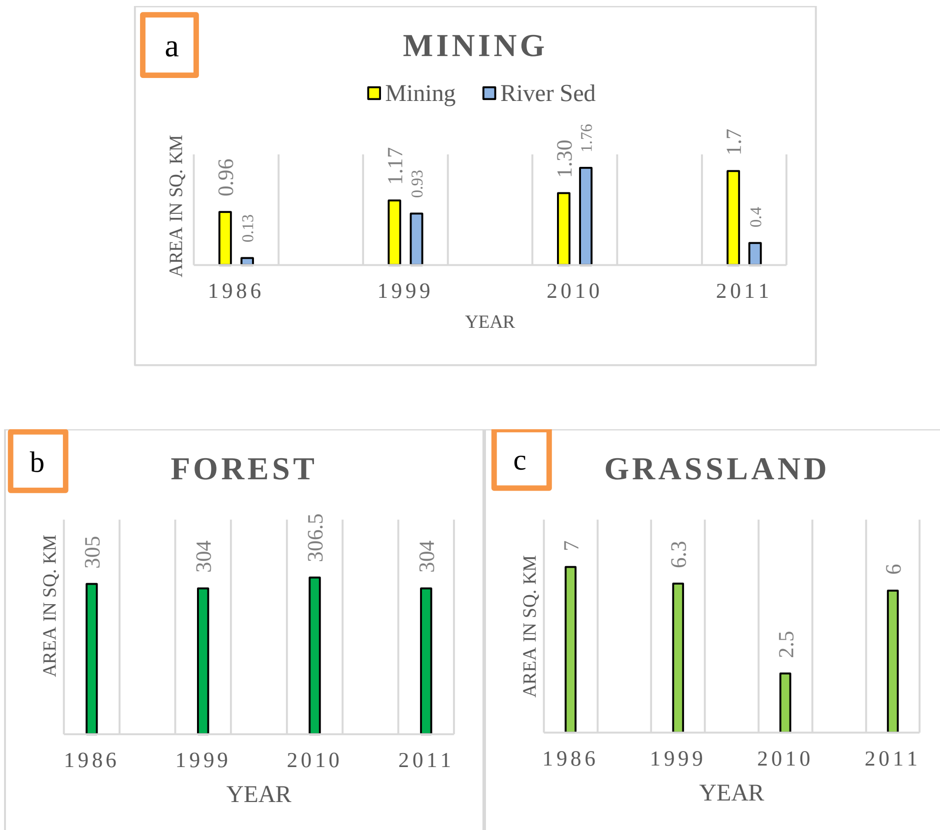


Figure 12: Vegetation cover and mining activities in 1986, 1999, 2010 and 2011

Similarly, figures 14:b and 14:c show the change in total area of forest and grassland respectively. In figure 14:b, the increase in artisanal mining activities might be one cause for the decline in vegetation cover. The forest class fell by 1 square km in those

25 years. The increase of forest area in 2010 may be due to the misclassification of grassland as forests, since the grassland area in 2010 was 3.5 square km less than the 2011 grassland class. Meanwhile, the gradual decline in grassland area between 1986 and 2011 may signify the conversion from grassland cover to other activities such as mining. For the most part, croplands were basically incorporated and classified in the grassland class, therefore drop in grasslands could be attributed to the shift of practice from agriculture to mining.

6. CONCLSION

Artisanal small scale gold mining activities have substantial effects on the environment. Among other problems, the loss of vegetation cover due to the expansion of mining sites has been a significant problem in the Amazonian Guyana. The area selected for this study is around the village of Jawalla, in the Upper Mazaruni river basin which is located in the western part of the country. This area has undergone considerable landuse and landcover changes over the past few decades.

As the Guyanese government strives to achieve the REDD+ goals and control deforestation, there have been disputes between the indigenous people and the authorities which has made the annual forest loss in the area difficult to estimate. Given these situations, the main objective of this study was to 1. detect, classify and map landuse/landcover changes between 1986 and 2011, 2. quantify the expansion of mining areas over those years and 3. estimate the forest or vegetation loss in those 25 years.

In order to achieve these goals, a two folded methodology was implemented. In the first phase, the Landsat images of 1986, 1999 and 2010 were processed using maximum-likelihood supervised classification approach to produce LULC maps. In order to enhance the classification, the results were further processed using knowledge engineer classifier. Although, these LULC maps provided helpful information on the spatial and temporal expansion of mining areas and decline of vegetation cover in the study area, the overall accuracy was low. This is mainly due to the relatively course resolution (30 meter) of the input images and the presence of persistent cloud cover, which undermined the total areas of several classes.

In the second phase, the RapidEye image with 5m resolution was segmented and classified in eCognition using an object based image analysis approach. Even if the emphasis was on mining sites and vegetation cover, a total of 11 LULC classes were produced. The use of higher resolution imagery coupled with OBIA's capability in considering both spectral and spatial components provide a means to distinguish the different sized pits with better accuracy. The 67%-100% producer's accuracy and 79%-100% users' accuracy achieved with this technique also reflects this fact.

Finally examining the research assumptions was essential. The first assumption was that pixel-based and OBIA can be used to quantify the extent of forest loss from ASM. This was evident from the results that showed artisanal small scale mining areas have doubled from 0.96 square km in 1986 to 1.9 square km in 2011, while vegetation cover fell down by 13.5 square km over the same period of time. Therefore, it was reasonable to support the first assumption of the study.

The second assumption predicted that OBIA can be more effective than pixel-based in distinguishing different levels of ASGM activities. The robust nature of the approach coupled with the ability of adding an expert knowledge has resulted in a higher overall accuracy when compared to the pixel-based approach. It should also be noted that, a higher resolution image was used with the OBIA, which further substantiated the accuracy. Hence, as was evident from the inclusion of additional class (alluvial pits, settlements and barren land), it was realistic to support the second assumption as well.

Finally, although the results of the LULC presented a fair accuracy, it should be noted that, without actual ground control points, it is difficult to be certain and the results may not provide accurate information about the conditions on the ground. This is because, the researchers were not able to take ground control points in the study area. However, the future work will consider addressing these limitations to obtain better output. Furthermore, the fact that some mining sites along the river were abandoned, would lead to further research on the conversion of LULC from mining to other classes.

References:

Brosius, P. J., Tsing, A. L. & Zemer, C., 2005. Maps Power and the Defense of Territory: The Upper Mazaruni Land Claim in Guyana. In: M. Colchester, ed. *Communities and Conservation: Histories and Politics of Community-based Natural Resource Management.* Walnut Creek: Alta Mira Press, pp. 271-303.

Chakravarty, S., Ghosh, S. & Suresh, A., 2012. Deforestation: Causes, Effects and Control Strategies. In: C. A. Okia, ed. *Global Perspectives on Sustainable Forest Management.* s.l.:s.n., pp. 1-28.

Clifford, M. J., 2011. Pork knocking in the land of many waters: Artisanal and small-scale mining (ASM) in Guyana. *Resources Policy,* Issue 36, pp. 354-362.

Colchester, M. & La Rose, J., 2010. *Our Land, Our Future: Promoting Indigenous Participation and Rights in Mining, Climate Change and other Natural Resource Decision-making in Guyana,* Geogetown: Amerindian People's Association.

Colchester, M., La Rose, J. & James, K., 2002. *Mining and Amerindians in Guyana: Exploring Indegenous Perspective on Consultation and Engagement within the Mining Sector in Latin America and the Carribean,* Ottawa: The North-South Institute.

Colson, B., 1996. *Encyclopedia of World Cultures.* [Online]
Available at: http://www.encyclopedia.com/doc/1G2-3458001138.html
[Accessed 01 11 2014].

Congalton, R. G., 1991. A Review of Assessing the Accuracy of Classifications of Remotely Sensed Data. *Remote Sensing of Environment,* Volume 37, pp. 35-46.

Congalton, R. G. & Green, K., 2009. *Assessing the Accuracy of Remotely Sensed Data: Principles and Practices.* 2nd ed. Boca Raton: CRC Press.

Conservation International, Projekt Consult & WWF for a Living Planet, 2013. *Guyana's Extractive Industry Sector (EIS) A Synopsis of Issues and Recommendations for the mining sector as a Sustainable Element of Guyana's Low Carbon Development Strategy,* s.l.: s.n.

Docena, H., 2010. Deforestation through mining subsidized by CDM project. *WRM's bulletin Nº 161.*

Dooley, K. & Griffiths, T., 2014. *Indigenous Peoples' Rights, Forests and Climate Policies in Guyana: a special report*, Georgetown: Amerindian People Association and Forest Peoples Programme.

Dow, J., Radzik, V. & Macqueen, D., 2009. *Independent Review of the Stakeholder Consultation Process for Guyana's Low Carbon Development Strategy (LCDS).* [Online]
Available at: http://pubs.iied.org/pdfs/G02590.pdf
[Accessed 2 5 2015].

Düzgün, H. Ş. & Demirel, N., 2011. *Remote Sensing of the Mine Environment.* London: Taylor & Francis Group.

Gao, Y. et al., 2006. Comparison of pixel-based and object-oriented image classification approaches—a case study in a coal fire area, Wuda, Inner Mongolia, China. *International Journal of Remote Sensing*, 27(18), p. 4039–4055.

George, L. & Almås, O., 2015. *Amerindian lands and resources in the Upper Mazaruni under siege.* [Online]
Available at:
http://www.forestpeoples.org/sites/fpp/files/publication/2014/06/guyanasection2.pdf

Giri, C. P., 2012. *Remote Sensing of Landuse and Landcover: Principles and Applications.* Boca Raton: Taylor & Francis.

Guyana Geology and Mines Commission, 2011. *Guyana Mineral Production Declared.* [Online]
Available at: http://www.ggmc.gov.gy/Documents/MinProduction1979-2010.pdf
[Accessed 03 04 2014].

Guyana Times, 2014. *News: Young people leaving agriculture for gold mining.* [Online]
Available at: http://www.guyanatimesgy.com/2014/06/03/young-people-leaving-agriculture-for-gold-mining-baksh/
[Accessed 20 4 2015].

Hansen, M. C. et al., 2013. *Global Forest Change.* [Online]
Available at: http://earthenginepartners.appspot.com/science-2013-global-forest
[Accessed 02 04 2015].

Hennessy, L., 2014. Where There Is No Company: Indigenous Peoples,Sustainability, and the Challenges of Mid-Stream Mining Reforms in Guyana's Small-Scale Gold Sector. *New Political Economy*, pp. 126-153.

Hentschel, T., Hruschka, F. & Priester, M., 2003. *Artisanal and Small-Scale Mining: Challenges and Opportunities,* London: IIED.

Hilson, G., 2002. The Environmental impact of small-scale gold mining in Ghana: identifying problems and possible solutinos. *The Geographical Journal,* pp. 57-72.

Hruschka, F. & Echavarria, C., 2011. *Rock solid chances for responsible artisanal mining,* Medellin : Communitymining.org.

Huber, O., Gharbarran, G. & Funk, V. A., 1995. *Preliminary Vegetation Map of Guyana.* [Online]
Available at: http://botany.si.edu/bdg/vegmap.html
[Accessed 10 11 2014].

IHRC, I. H. R. C., 2007. *All That Glitters: Gold Mining in Guyana; The failure of Government Oversight and the Human Rights of Amerinidian Communities,* Cambridge, Massachusetts: Human Rights Program, Harvard Law School.

ILO, 2003. *Facts of Small Scale Mining.* [Online]
Available at: http://www.ilo.org/global/resources/WCMS_067582/lang--en/index.htm
[Accessed 06 10 2014].

International Human Rights Clinic, 2007. *All That Glitters: Gold Mining in Guyana,* Cambridge: Harvard Law School.

ITTO, I. T. T. O., 2011. *Guyana Profile.* [Online]
Available at:
www.itto.int/direct/topics/topics_pdf_download/topics_id=2653&no=2&file_ext=Guyana+profile.pdf
[Accessed 20 04 2015].

Jensen, R. R., Gatrell, J. D. & McLean, D., 2007. *Geo-Spatial Technologies in Urban Environments:Policy, Practice, and Pixels.* 2 ed. New York: Springer-Verlag Berlin Heidelberg.

Kusimi, J. M., 2008. Assessing land use and land cover change in the Wassa West District of Ghana using remote sensing. *Geo Journal,* Volume 71, pp. 249-259.

Lowe, S., 2005. *Situation Analysis Report: small-scale gold mining in Guyana,* Georgetown: WWF.

Luneta, R. S. et al., 1991. Remote Sensing and Geographic Information System Data Integration: Error Sources and Research Issues. *Photogrammetric Engineering & Remote Sensing,* 57(6), pp. 677-687.

Marschallinger, R. & Hofmann, P., 2010. The application of Object Based Image Analysis to Petrographic Micrographs. *Microscopy: Science, Technology, Applications and Education,* pp. 1526-1532.

Ministry of Legal Affairs , G., 1989. *Mining Act.* [Online]
Available at: http://legalaffairs.gov.gy/information/laws-of-guyana/708-chapter-6501-mining
[Accessed 04 04 2015].

MNRE, (. o. N. R. a. E., 2013. *Guyana's 3rd National Report on Deforestation.* [Online]
Available at:
http://www.nre.gov.gy/Guyanas%203rd%20National%20Report%20on%20Deforestation.%20November%2001%202013.html
[Accessed 08 10 2014].

Myint, S. et al., 2011. Per-pixel vs. object-based classification of urban land cover extraction using high spatial resolution imagery. *Remote Sensing of Environment,* 115(5), pp. 1145-1161.

NAG, N. A. o. G., 1989. *Mining Act PL1.* s.l.:s.n.

Pagot, E., Pasaresi, M., Buda, D. & Ehrlich, D., 2008. Development of an object-oriented classification model using very high resolution satellite imagery for monitoring diamond mining activity. *International Journal of Remote Sensing,* 29(2), pp. 499-512.

Persaud , A. & Telmer, K., 2013. *artisanalgold.com.* [Online]
Available at: http://artisanalgold.blogspot.com/2013/04/historical-and-modern-

government.html
[Accessed 30 September 2014].

Sarmadian, F., Alavi Panah, S. K., Heck, R. J. & Matinfar, H. R., 2007. Comparisons of Object-Oriented and Pixel-Based Classification of Land Use/Land Cover Types Based on Lansadsat7, Etm+. 2(4).

Sonter, L. J., Barrett, D., Moran, C. & Soares-Filho, B., 2013. *Mining, deforestation and conservation opportunities: A case study of the Quadrilátero Ferrífero land use change dynamics.* Foz do Iguaçu, INPE, pp. 6300-6307.

Staff, S., 2010. *Mining deforestation nearly tripled between 2000-08.* s.l.:s.n.

Swenson, J., Carter, C., Domec, J.-C. & Delgado, C., 2011. Gold Mining in the Peruvian Amazon: Global Prices, Deforestation, and Mercury Imports. *PLos ONE*, 6(4).

The Columbia Encyclopedia, 6th ed., 2014. *Mazaruni.* [Online]
Available at: https://www.questia.com/read/1E1-Mazaruni/mazaruni

Thomas, C. Y., 2009. *University of Guyana: Institute of Development Studies.* [Online]
Available at: http://idsguyana.org/articles/professor-clive-thomas/new-menu.html
[Accessed 09 May 2015].

Whitaker, J. O. & Amlaner, C. J., 2012. *Habitats and Ecological Communities of Indiana: Presettlement to Present.* Bloomington: Indiana University Press.

World Bank, 2013. *Artisanal and Small-Scale Mining.* [Online]
Available at: http://www.worldbank.org/en/topic/extractiveindustries/brief/artisanal-and-small-scale-mining
[Accessed 06 10 2014].